ELECTRICAL FAULT DETECTION ON DOWNED DC TROLLEY LINES

J. S. Peterson
G. P. Cole

NIOSH
Pittsburgh, PA

Abstract. The National Institute for Occupational Safety and Health (NIOSH), Pittsburgh Research Center (PRC), has conducted research to improve electrical fault detection on coal mine direct current (dc) trolley systems. Present circuit breaker protection systems are current-magnitude-based and cannot discern between normal traffic and high resistance electrical faults. Tests were conducted at cooperating mines to assist in developing a neural-network-based detection algorithm for distinguishing between electrical faults and normal operation. The Fast Fourier Transform of the trolley rectifier current signature served as baseline data for the neural network. During field tests, the algorithm performed with greater than 90% accuracy.

Introduction

Direct current (dc) trolley systems move personnel, supplies, and coal in roughly 50 U.S. mines. A suspended trolley line energized at 300 or 600 Vdc provides electrical power while a system of steel rails serves as the return path. Inductance of the trolley system is dependent upon the physical separation of the trolley line and the rail. Generally, for 300-V systems, it is 347 μH/1,000 ft and for 600-V systems, it is 368 μH/1,000 ft (Paice, 1973). Because haulage distances may extend for miles, significant inductances may be inherent in the trolley system. When roof falls and other accidents force the trolley line down near a ground return rail, this inductance facilitates arcing between the line and rail. Such arcing may be self sustaining at currents above 200 amps (Hall, 1978). Electrical accidents like this are not always preventable by conventional circuit breakers because the magnitudes of the currents involved may be significantly less than typical breaker trip settings. In 1989, a trolley system fire struck the Mathies mine near Pittsburgh, PA, and burned for one month before it was extinguished. In 1990, a similar fire at the Mathies mine prevented access to 30,000,000 tons of reserves and resulted in the closing of the facility. It has since reopened under new ownership.

NIOSH demonstrated a method to detect trolley faults in 1980 (Paice, 1980). This system required that a signal wire be suspended parallel to the trolley line, an oscillator to superimpose a 3-kHz signal on the trolley wire, and a filtering system on locomotives larger than 25 tons. The coal industry did not adopt the system because of the complexity and cost of the hardware. Advances in computer software have made it possible to employ rapid classification algorithms to detect obscure solutions. A detection algorithm running on a microprocessor-based system would be installed to monitor the dc current of the trolley rectifier. Its output would be analyzed to determine if there is any fault activity. If a fault is detected, an indicator signal would be provided to break the trolley circuit, or provide an audio or visual alarm. This approach eliminates the modification of the trolley line or its vehicles, lessening maintenance concerns and costs.

Data Collection and Signal Analysis

Development of a detection algorithm required several steps which included:

1. Configuring an adequate data acquisition system;
2. Using the data acquisition system to record the electrical signature (current and voltage) of normal traffic and induced faults at a cooperating mine;
3. Using the collected data to train and test a detection algorithm;
4. Returning to the cooperating mines and testing the detection algorithm.

It was necessary that the data acquisition system be light weight, versatile, and rugged enough to withstand less than optimal test conditions. Magnetic tape recording was initially considered as a viable option, and it was used for data collection early in the project. However, magnetic tape allowed for no onboard data analysis and this effectively eliminated it as an option. No off-the-shelf recording devices were found that met the particular requirements, so a unique system was developed in-house. The system was composed of a module to provide electrical isolation and signal gain, elliptic low-pass filters, an analog-to-digital converter (ADC), an industrial PC, and signal amplifiers (Figure 1). The isolation module provided electrical isolation between data channels and between data channels and ground. It also provided signal gain and attenuation for input signal scaling. Low-pass elliptic filters with switch selectable cutoff frequencies filtered out data signals whose frequencies were above those of interest. An 8-channel ADC recorded the data for use later during the analysis portion of the research. A ruggedized, 486-based 75-MHz PC housed the ADC and allowed on-board high-speed data collection and analysis. When needed, signal amplifiers boosted low level current shunt signals.

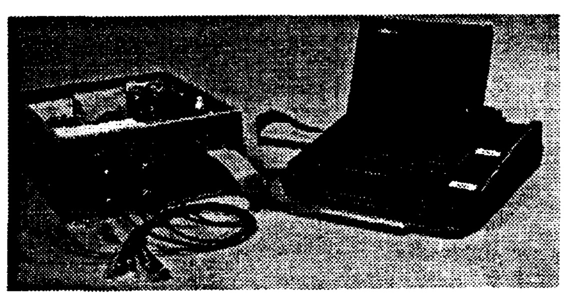

Figure 1. Custom data acquisition system used for field work

Figure 2 shows the hardware used for inducing resistive faults on a trolley system. This included multiple 0.3-ohm power resistors used to limit the fault current. A wooden and steel bracket was used to secure copper, steel, or aluminum electrodes in place. Copper fuse wire served as the initial current path between the electrodes. For bolted faults, the trolley line and rails were simply shorted together and did not induce arcing. A contactor switched the faults into the trolley circuit either by push button switch or via a fiber-optic isolated control switch.

Fast Fourier Transforms (FFT's) converted the test data from the time domain to the frequency domain for evaluation of the signal energy at the fundamental frequency (60 Hz) and its harmonics. Once this was done, a custom C-based software program converted the FFT results into training data for the detection algorithm. Software technology has evolved to the point where artificial neural networks (ANN's) are now viable tools for nonlinear applications such as this. Neural networks learn by example and must be "trained" on a particular problem. Data collected under known conditions, e.g., fault/no-fault, trains the ANN. The neural network then learns the relevant features of the data that discern between the possible inputs. Later, the ANN is tested with data not used for training to find if the network will make the correct evaluation.

Field Work

Recording Sessions

Several Pennsylvania and West Virginia coal mines were visited to conduct tests of 300 and 600 Vdc trolley systems under assorted operating conditions. These conditions comprised traffic present on the system at any given time, large and small vehicle traffic, pump activity, and heavy, intermediate, and minimal current draw. These tests represent the no-fault portion of the data collected. Duplication of these tests with the inclusion of an induced resistive or bolted fault composed the faulted data tests. Carefully selected sites both on the surface and underground and at various distances from the trolley rectifier served as fault locations. This ensured observation of a variety of possible test conditions.

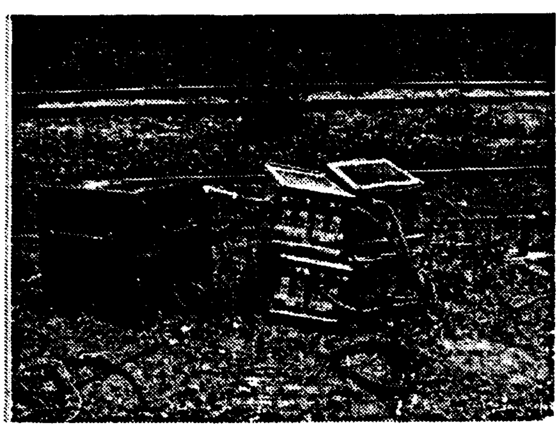

Figure 2. Trolley system fault hardware.

Figure 3 illustrates an actual data file of trolley current plotted vs. time. This field test covered the time before, during, and after an induced resistive fault. Besides the fault, there was minimal background traffic on the system as well. While this fault arced for approximately 14 sec, the peak current of roughly 650 amps was never close to the circuit breaker setting of several thousand amperes. Figure 4 shows the average FFT's of data taken from the data file shown in Figure 3. For each FFT, four successive, 1/60-sec time windows of data (1,024 points) were selected for analysis. The solid plot is from data collected during the induced fault while the dashed curve is data collected before the fault. The FFT of the faulted data exhibits significantly more leakage than the no-fault data. When leakage occurs, the energy component at one frequency leaks into the vicinity of other energy components resulting in spectral smearing. This has the effect of broadening the lobes (spectral lines or peaks) of the FFT and making them less distinct. For comparison, similar evaluations produced Figure 5. Here, an average FFT of a locomotive returning empty trolley cars underground is shown. During this period, trolley current draw was roughly 750 amps. The significant leakage so evident in the faulted data of Figure 4 is not present in this plot, i.e., the lobes of this FFT are distinct.

The detection network developed keyed upon the frequency content of the current spectrum, ranging from 0 to 10 kHz. More precisely, several networks were developed that keyed upon different bands in this range. They included 0 to 1,380 Hz, 1,440 to 2,820 Hz, and 0 to 9,960 Hz. The network with the best results, and discussed later, was the network keying upon the 1,440- to 2,820-Hz frequency band. Several tests were undertaken to examine higher frequency components with poor results. Detection networks were built keying upon the 10- to 20-kHz band but had double

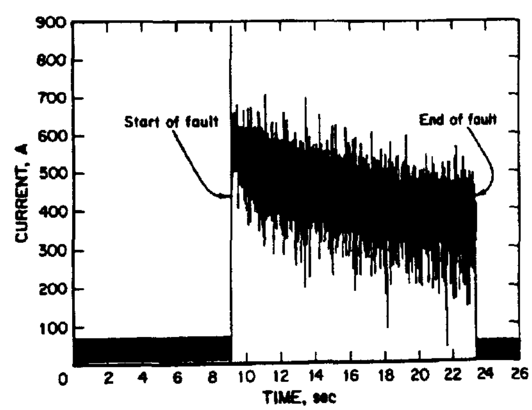

Figure 3. Induced fault and traffic current vs. time.

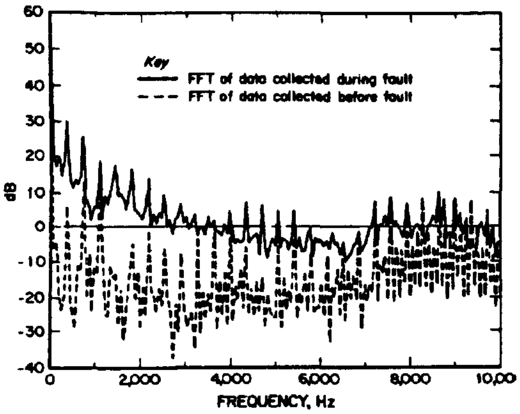

Figure 4. Induced fault and traffic current averaged Fast Fourier Transforms.

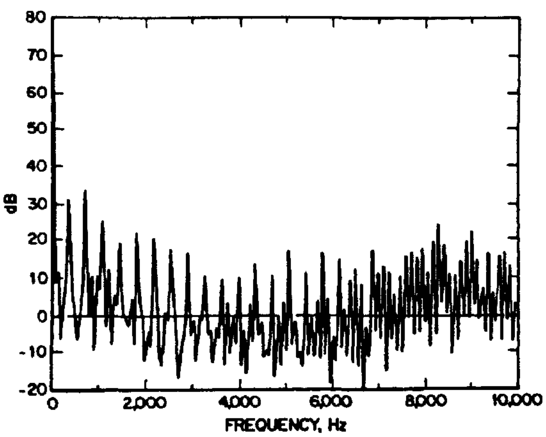

Figure 5. Fast Fourier Transform of current data collected during a locomotive returning empty trolley cars to the mine.

the RMS errors due to less data content. Plots of FFT's extending up to 40 kHz (Figure 6) also showed no consistent markers unique to a fault. Therefore, all analysis was limited to frequency components within the 0- to 10-kHz range. This range shows the greatest spectral variations between normal and faulted conditions and the highest signal to background noise ratio.

Monitoring Sessions

After rigorous training and testing in the laboratory, the detection algorithm was installed on the ruggedized PC for field testing under conditions similar to those of the recording sessions. Raw data in 1/15-sec bursts were collected, analyzed, and then classified as either a normal or faulted condition. The PC then provided a visual and audio beep indication of the trolley systems status. This process continued repeatedly while the algorithm monitored the trolley system.

Results

The resulting artificial neural network monitoring tests provided information on both the field testing and training accuracy of the network. The raw network output and its variances between the set values of ± 1 (normal or fault) provided important information. As the neural network predictions gravitated toward ± 1, it signified a high level of confidence in the classification. When the output shifted toward zero, network confidence decreased and indicated possible weak areas in the training set. Additional training patterns could then be added to help improve network accuracy.

For deployment purposes, however, this amount of detail was not necessary. The required output from the detection network was a normal or fault indication. Another tradeoff must also be considered. False alarms in the production-oriented environment of coal mine haulage could result in costly and unnecessary interruptions. To account for these factors, thresholding and rounding of the raw network output helped eliminate false alarms at the cost of decreasing overall accuracy. The network output is forced to $+1$ (normal) or -1 (fault) only. The threshold represents the minimum prediction value to be treated as a valid fault classification. Figure 7 illustrates this scheme using a threshold of (-0.5). For comparison purposes, the raw artificial neural network output and the 'normalized' output are superimposed above the current wave of a monitoring test. Region A is where the fault occurs in this test amid normal loading from the locomotive. When deployed, the detection network runs in an on-line mode examining the system approximately once a second. Therefore, a network with a classification rate of 75% and no false alarms is much more beneficial than a network with a rate of 90% with some false alarms. This network will not false trip the breaker and has a 75% chance each successive second of detecting the fault, while still providing a strong measure of protection. As an additional measure to further decrease the chance of false alarms, the system could be set to

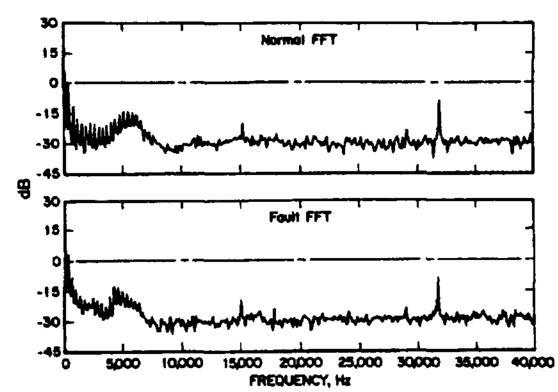

Figure 6. Comparison of normal and faulted Fast Fourier Transforms, dc to 40 kHz.

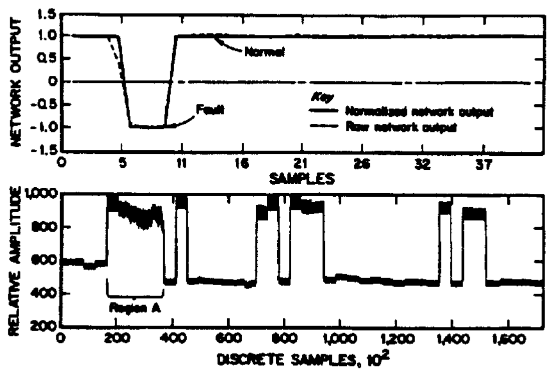

Figure 7. Comparison of neural network classification and current signal.

wait for several fault indications in sequence before activating an alarm or circuit breaker. This additional step would slow the response time to approximately once every 3 sec.

The performance of the final mine-specific network proved to be excellent. Accuracy of the network is calculated based upon the results from running in a 'monitoring' mode. This was done to keep data used for training purposes isolated from the data used for testing and verification. In 62 monitoring tests, the network correctly classified the normal/fault status of the system with an accuracy of 97.9%. Of the 2.1% wrong classifications, 1.9% were missed fault classifications and 0.2% were false alarms. This means that for approximately each second a fault exists on the system, there is a 97.9% change that it will be detected. The monitoring tests generated 4,338 patterns for the network, covering approximately 30 minutes of on-line detection time. Each test was conducted in the same manner as a recording test with the exception that the data feeds directly into the detection network where it displays the fault status. Also important to note is that all of the false alarms were single instance occurrences. These are eliminated if there is no alarm until fault detection occurs two or three times in sequence as discussed earlier.

It was originally planned that a single neural network be trained to generalize across different mine dc trolley systems. This was not accomplished for several reasons. The data gathered from the different mines may not have provided a sufficient generalized profile. Further, the variations between mines may be too complex to model with the existing technique. These variations can include different rectifier types, operating voltages, equipment running on the system, and system size and complexity. The network discussed in this paper is rectifier and arcing fault specific. That is, it was trained solely on patterns obtained from a single mine rectifier and induced arcing faults. A detection network for another mine was successfully trained using bolted and arcing fault patterns but lacked sufficient verification tests for adequate discussion here. To deploy this detection scheme to mines would require training the network for each individual mine system. Deploying the network manually or in a self-learning configuration could achieve this.

Summary

The monitoring test results have displayed the artificial neural network's ability to accurately detect faults on dc trolley systems. Arcing faults are successfully detected using only the frequency content of the rectifier current and the imposed fault signal. Used with the existing over-current circuit breakers this scheme can add another layer of protection for both mine personnel and material. Self sustaining arcs caused by roof falls or similar events could be extinguished before igniting adjacent material and causing fire hazards. This system can be implemented using a self-contained microprocessor mounted on each rectifier where it would monitor the current, representing an improvement over prior techniques.

Acknowledgments

The authors thank Michael R. Yenchek, for his role as principle investigator of the project, Arthur J. Hudson, for his instrumentation work, and Kevin Schuster (retired) and George Persetic, for their assistance during field visits. All are employees of NIOSH.

References

Hall, P. M., Myers, K., and Vilchek, W. S., 1978, "Arcing Faults on Direct Current Trolley Systems", Proceedings of the 4th West Virginia University Conference on Coal Mine Electrotechnology, Morgantown, WV, pp. 21-1-21-19.

Paice, D. A., 1980, "Discriminating Circuit Breaker System for Trolley Wire Protection", (Westinghouse Electric Corp., contract H0122058); USBM OFR 73-79, NTIS PB-297-832, 35 pp.

Paice, D. A., Shimp, A. B., and Putkovich, R. P., 1973, "Circuit Breaker Development and Applications", (Westinghouse Electric Corp., contract H0122058); USBM Contract Phase I Report, pp. 2-15.